

## FRVT 1:N Remaining Errors in Cooperative FR: Implications for Quality Assessment

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IFPC 2018 @ NIST  
November 29, 2018



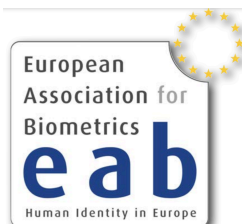
| IFPC 2018 - Tuesday Nov 27 |    |  | IFPC 2018 - Wednesday Nov 28 |  |  | IFPC 2018 - Thursday Nov 29  |  |  |
|----------------------------|----|--|------------------------------|--|--|--|--|--|
| Government and Borders     |    | 0800 Arrive + Registration: 08:30 Welcome + Logistics  |                              |  | 0800 Arrive + Registration 08:30: Start + Review Day 1 |  |  | 0800 Arrive + Registration 08:30: Start + Review Day 2 |
|                            | 01 | 0840 Arun Vemury, DHS Science + Technology Directorate: Welcome + DHS context  | 19                           | 0835 Lars Ericson, IARPA: Overview of the Odin program on presentation attack detection  | 38   | 0840 Amir Arien, Biometrics Registration Authority, Israel: The Israeli National Biometric Project   |  |  |
|                            | 02 | 0850 Dan Tanciar, US Customs and Border Protection: CBP use of Facial Recognition in Development of a Biometric Entry/Exit System              | 20                           | 0855 Ralph Breithaupt, BSI: Presentation Attack Detection & Morphing: New developments in biometric security testing and certification | 39   | 0905 Delia McGarry and Stephen Melsom, U.S. Department of State: Image manipulation detection and effects of perspective distortion on face identification |  |  |
|                            | 03 | 0915 Oliver Bausinger, BSI, Smart Borders: EES, ETIAS and Interoperability - towards a unified identity management for Third Country Nationals | 21                           | 0920 Rasa Karbauskaitė, Frontex: Morphing and other related vulnerabilities for border control   | 40   | 0930 Shashi Samprathi, Australian Passport Office DFAT: Update on uses of face recognition   |  |  |
|                            | 04 | 0940 Anna Stratmann, BSI: Biometric processes of the Entry Exit System   | 22                           | 0940 Max Dermann, Bank of New Zealand: Evaluation of face PAD solutions - a bank's journey   | 41   | 0955 Andreas Wolf, Bundesdruckerei: ICAO's technical report on portrait quality  |  |  |
|                            |    | 1005 Break   | 23                           | 1005 Gert Jan de Nijs, Dutch Vehicle Authority: Creating a process to prevent photo fraud  |  | 1020 Break   |  |  |
|                            | 05 | 1035 Markus Nuppeney, BSI: Automated Border Control (EasyPASS): Monitoring the system performance  | 24                           | 1055 Fons Knopjes, Passports Netherlands: SOTAMD: A European state of the art morph detection program                                  | 42   | 1050 Mickey Cohen, Shanit: Privacy, Security and facial de-identification aspects  |  |  |
| Fast Cap                   | 06 | 1100 James L. Wayman, John P. Bowes and Joshua Abraham, 2018 for Department of Home Affairs, Australia, SmartGate(TM) Update                   |                              | 1120 Karl Kanto, The National Police Board of Finland: Morph detection experiments with large data sets                                | 43   | 1110 Arun Ross, Michigan State University: Semi Adversarial Networks for Face De-identification  |  |  |
|                            | 07 |  | 26                           | 1145 Christoph Busch, HDA/NTNU: Morphing attack detection overview   | 44   | 1135 Stephane Gentic, Idemia: TBA  |  |  |
|                            | 08 | 1150 John Howard, SAIC: Evaluation of rapid face capture devices   | 27                           | 1210 Marta Gomez-Barrero, Hochschule Darmstadt: Vulnerability Evaluation of Presentation + Morphing Attacks                            | 45   | 1200 Thorsten Thies, Cognitec: Effects of wrong ID labels  |  |  |
| FR in Police               | 09 | 1215 Ilan Arnon, Face4Systems: Face recognition on-the-move: Case Studies  | 28                           | 1230 Mei Ngan, NIST: FRVT Face Morph Detection Evaluation  | 46   | 1225 Brendan Klare, Rank One Computing: Emerging applications in commercial face recognition   |  |  |
|                            |    | 1240 Lunch   |                              | 1245 Lunch   |  | 1240 Lunch   |  |  |
|                            | 10 | 1340 Geoff Whitaker, DSTL UK: ISO 30137 video surveillance and OSAC ASTM update E3115  | 29                           | 1400 Jonathon Phillips, NIST: Recognition Accuracy of Forensic Examiners, Super-recognizers, and Algorithms                            | 47   | 1340 Christoph Busch, Hochschule Darmstadt: Measures for benchmarking indexing algorithms  |  |  |
| Demographics               | 11 | 1405 Mark Branchflower, Interpol: Face recognition in Transnational Crime  | 30                           | 1420 Richard Vorder Bruegge, FBI: Improving the Process: What could help forensic examiners make better decisions?                     | 48   | 1405 Michael Thieme, Novetta: Impact of Non-Facial Regions on FR Performance   |  |  |
|                            | 12 |  | 31                           | 1445 Eilidh Noyes, University of Huddersfield: What is a super-recognizer?   | 49   | 1430 Tony Mansfield, NPL: ISO/IEC 30137-2 Biometric video surveillance - testing and reporting   |  |  |
|                            |    | 1430 Break (cafeteria closes at 1500)  |                              | 1510 Break (cafeteria closes at 1500)  |  | 1450 Break (cafeteria closes at 1500)  |  |  |
|                            | 13 | 1500 John Campbell, Bion Biometrics: ISO/IEC 22116 Differential impacts of demographics in biometric systems                                   | 32                           | 1540 Carina Hahn: NIST: Issues on measuring facial forensic apprenticeship   | 50   | 1520 Marek Rejman-Greene, IdentityForServices: Design and management of reliable services using face recognition   |  |  |
|                            | 14 | 1520 Yevgeniy Sirotni, SAIC: Estimating relative skin reflectance and measuring its effect on recognition.                                     | 33                           | 1605 David White, UNSW-Sydney: Incorporating human perceptual expertise in face identification systems                                 | 51   | 1540 Chris Malec, DSTO: Australian government FR algorithm performance testing   |  |  |
|                            | 15 | 1545 Mike King, Florida Institute of Technology: Demographic effects in face recognition   | 34                           | 1630 Carlos Castillo, Uni. of Maryland: DCNNs for unconstrained face recognition   | 52   | 1605 Matt Pruitt, NEC: Getting the Best Facial Image in an Uncontrolled Environment: The Effect of User Experience on Facial Quality and Match Scores      |  |  |
|                            | 16 | 1610 Clare Garvie, Center on Privacy & Technology Georgetown Uni.: Consequences of differential impacts  | 35                           | 1655 Alice O'Toole, UT Dallas: Understanding face representations in deep convolutional neural networks: Face Space Theory evolves     | 53   | 1630 Nathan Kalka + Brianna Maze, Noblis: Curating large-scale face recognition benchmark test sets  |  |  |
|                            | 17 | 1635 Patrick Grother, NIST: Demographic dependencies in contemporary face recognition algorithms   | 36                           | 1720 Neal Gieselmann, Aware Inc.: Tools for human face comparison  | 54   | 1700 Patrick Grother, NIST: FRVT 2018 and the errors that remain in FR systems: Future Image Quality Standardization                                       |  |  |
|                            | 18 | 1700 Panel on Demographics: John Campbell, Clare Garvie, Patrick Grother, Mike King, Yevgeniy Sirotni  | 37                           |  |  |  |  |  |
|                            |    | Talks: 16. Dress code: Business casual, face masks   |                              | Talks: 18 Social Event 6PM: Dogfish Ale House opposite NIST  |  | Talks: 17 Adjourn: Until 2020  |  |  |

# NIST



**Homeland Security**  
Science and Technology

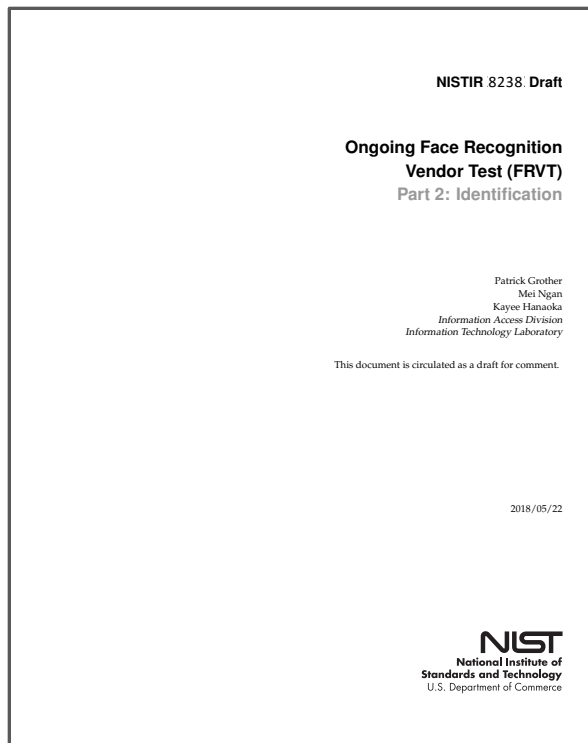
**NPL**  
National Physical Laboratory



## FRVT 1:N 2018:

The largest public independent face  
recognition test ever conducted

# Phase 1+2 report availability



## Interagency Report 8238

- Published 2018-11-26

Attributes accuracy with vendor names.

Revision follows 2019-01

- Add result for Phase 3 algorithms 2018-10-30
- Compare enrollments styles
  - Consolidated
  - Unconsolidated
- Add ageing
- Add selectivity metric
- Delete extraneous images
- Larger database



# Participation in Phase 1+2 (June 2018)

45 Developers of 127 Algorithms from 13 countries

- » 3divi (RU)
- » Alchera (KR)
- » Aware (US)+
- » Ayonix (JP)
- » Camvi (US)
- » Cogent Gemalto (FR)+
- » Cognitec (DE)
- » Dermalog (DE)+
- » Ever AI (US)
- » Eyedea (CZ)
- » Glory (JP)
- » Gorilla (CN)
- » HB Innovation (KR)
- » HIK Vision (CN)

- » Idemia (FR)+
- » Imagus (AU)
- » Incode (US)
- » Innovatrics (SL)+
- » Innovation Sys. (RU)
- » Megvii / Face++ (CN)
- » Microfocus (US)
- » Microsoft (US)+
- » NEC (JP)+
- » Neurotechnology (LI)+
- » NTechLab (RU)
- » Rank One (US)
- » Real Networks (US)

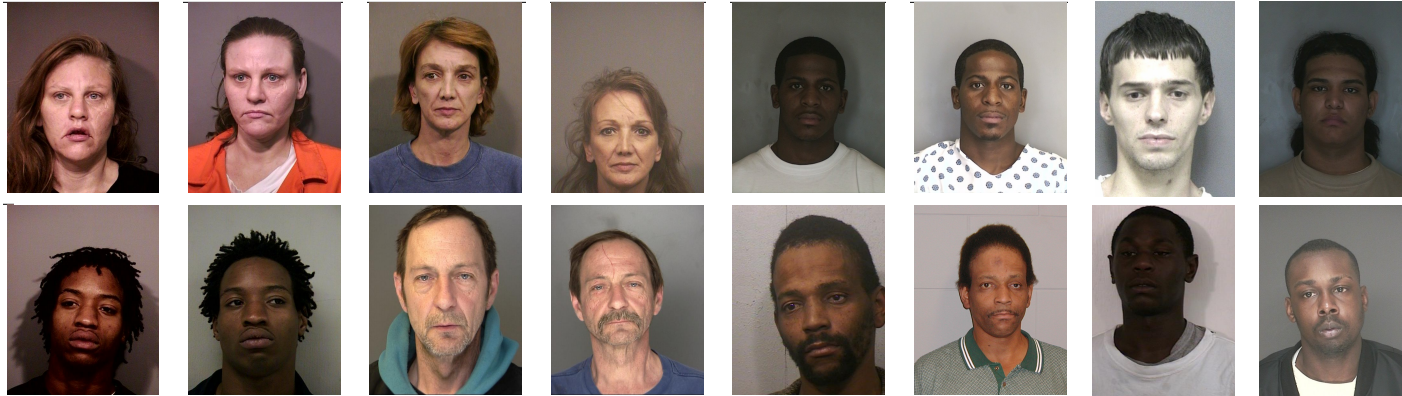
- » Shaman (US)
- » SIAT CASIA (CN)
- » Smilart (RU)
- » Synesis (RU)
- » Tevian (RU)
- » Tiger IT (BG)+
- » Tong Yi Trans (CN)
- » Vigilant Solutions (US)
- » Visidon (FI)
- » Visionlabs (RU)
- » Vocord (RU)
- » Yisheng (CN)
- » Yitu (CN)

+ = Multimodal

Not participating:

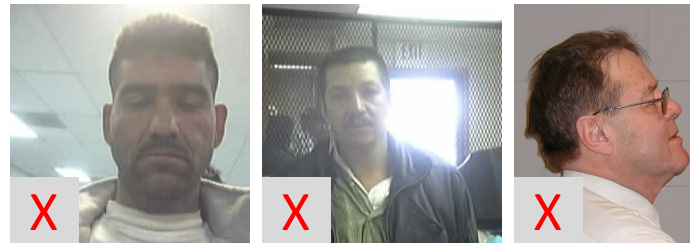
- « Amazon
- « Google
- « Facebook
- « IBM
- « Element AI
- « ... many others

# FRVT 2018 Mugshots / Booking / Charge Photos

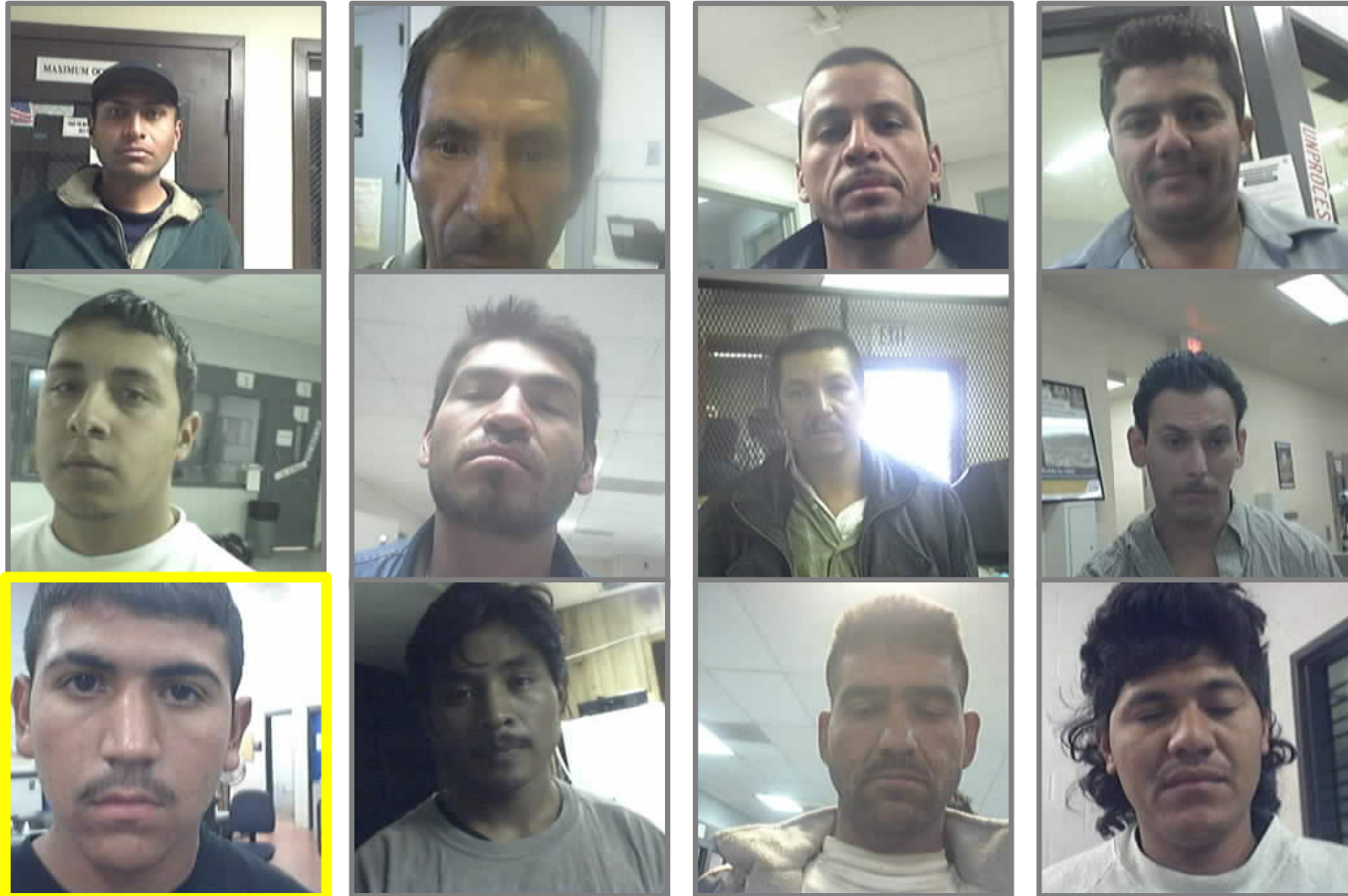


Images excluded:

1. Webcams (240x240, two shown)
2. Profile views, and others where intent was something other than frontal
3. Tattoos and other non-face images



## Operational Webcam images (these from MEDS DB)



| Mugshot-to-mugshot            |  |
|-------------------------------|--|
| Threshold set for FPIR = 0.01 | N = 1.6 million people<br>1.6 million images |
| Yitu                          | 0.011  |
| Microsoft                     | 0.013  |
| SIAT                          | 0.009  |
| Visionlabs                    | 0.022  |
| Ever AI                       | 0.023  |
| NTechLab                      | 0.024  |
| Idemia                        | 0.024  |
| Neurotechnology               | 0.030  |
| I-Systems                     | 0.035  |
| Cogent                        | 0.032  |
| NEC                           | 0.049  |
| Cognitec                      | 0.055  |
| HIK Vision                    | 0.056  |
| Megvii / Face++               | 0.058  |
| RankOne                       | 0.073  |



FNIR x 2.6

FNIR x 4.1

| Webcam-to-mugshot             |  |
|-------------------------------|--|
| Threshold set for FPIR = 0.01 | N = 1.6 million people<br>1.6 million images |
| Yitu                          | 0.028  |
| Microsoft                     | 0.053  |
| SIAT                          | 0.46 (!!)                                    |
| NTechLab                      | 0.065  |
| Megvii / Face++               | 0.067  |
| Neurotechnology               | 0.073  |
| Ever AI                       | 0.074  |
| Idemia                        | 0.079  |
| I-Systems                     | 0.080  |
| Visionlabs                    | 0.087  |
| NEC                           | 0.093  |
| Cogent                        | 0.100  |
| HIK Vision                    | 0.101  |
| Cognitec                      | 0.135  |
| RankOne                       | 0.187  |



# NIST

Developers  
of Most  
Accurate  
Algorithms:

Image  
Quality  
Matters

# Explaining residual errors from Microsoft and Yitu

## Of the 600 mates not returned on candidate lists of length 50

- » ~30% Body tattoo containing a face
- » ~15% Different person (truth labelling error)
- » Profile views
  - 40% for Yitu
  - 30% for Microsoft
- » Poor quality (scanned, dim, low contrast)
  - 15% for Yitu
  - 25% for Microsoft

Estimates from 600 false negatives, produced in  $M = 154549$  searches with  $\text{FNIR}(N, R, T) = 0.004$

- $N = 12,000,000$
- $R = 50$
- $T = 0$

## High-scoring non-mates Images above $T$ for $\text{FPIT}(T) = 0.001$

- » ~20% Confident different person (doppelganger)
- » Same person different ID
  - ~44% Confident
  - ~33% Not confident, twin?
  - ~2% Confident, same photo session
- » ~1% Scanned image, low quality

Estimates from 660 images involved in 330 false positives, produced in  $M = 331254$  searches with  $\text{FPIR}(N, T) = 0.001$

- $N = 12,000,000$

# New FRVT Result 2018-11-26: Profile searches



| N = 1.6M | Rank 1 Hit Rate | Rank 50 Hit Rate |
|----------|-----------------|------------------|
| ALG-A    | 91%             | 94%              |
| ALG-B    | 73%             | 85%              |
| ALG-C    | 17%             | 21%              |
| ALG-D    | 87%             | 93%              |

# Face quality drivers

## Background

- » Increased reliance on face recognition
- » Increased use globally, with interchange
- » Unlike fingerprint, iris, most face cameras are “dumb”, unaware of the face itself
- » Many photos deviate from ISO/ICAO
  - Subject appearance
  - Poor imaging
- » Better recognition algorithms
  - But fail with pose, resolution, demographics
- » Human “forensic” adjudication errors
- » New opportunities for image manipulation

## Short terms solutions

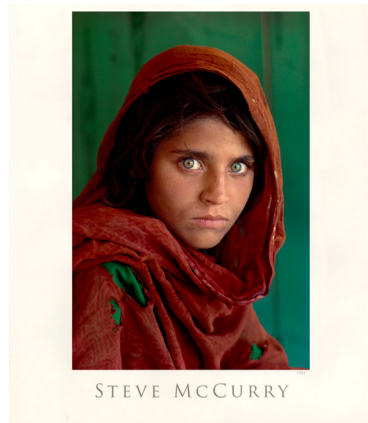
- » Better face recognition algorithms
- » Quality assessment
  - At capture time
  - Over an enterprise
  - Imaging systems

## Longer term solutions

- Face-aware capture devices



## The March of Time: Ageing



c. National Geographic, photographic portrait by  
journalist [Steve McCurry](#), 1984

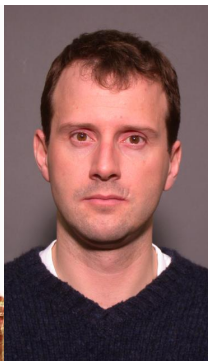


# Ageing

2002-08



2004-10



2010-05



2012



2013-08

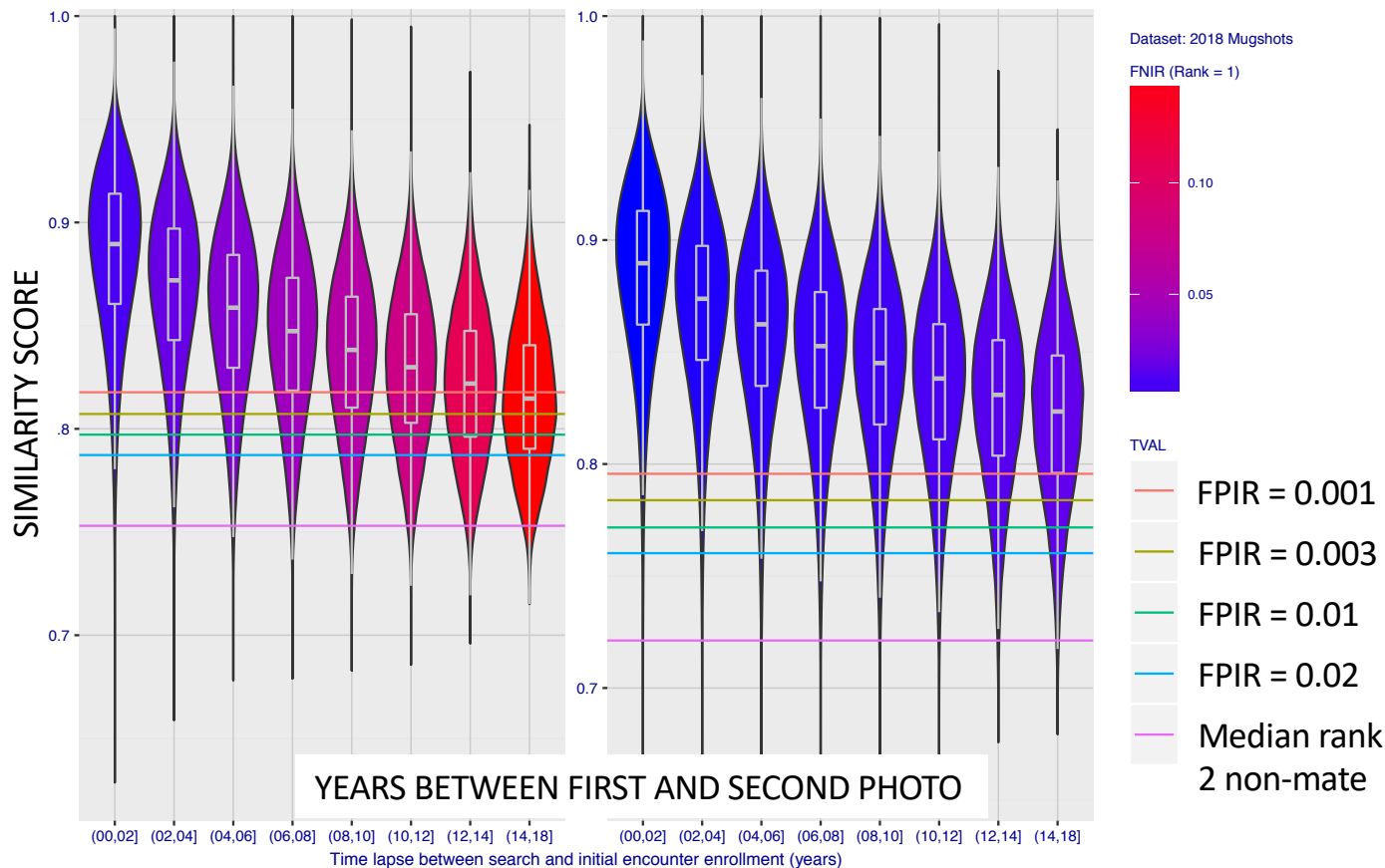


2018-06

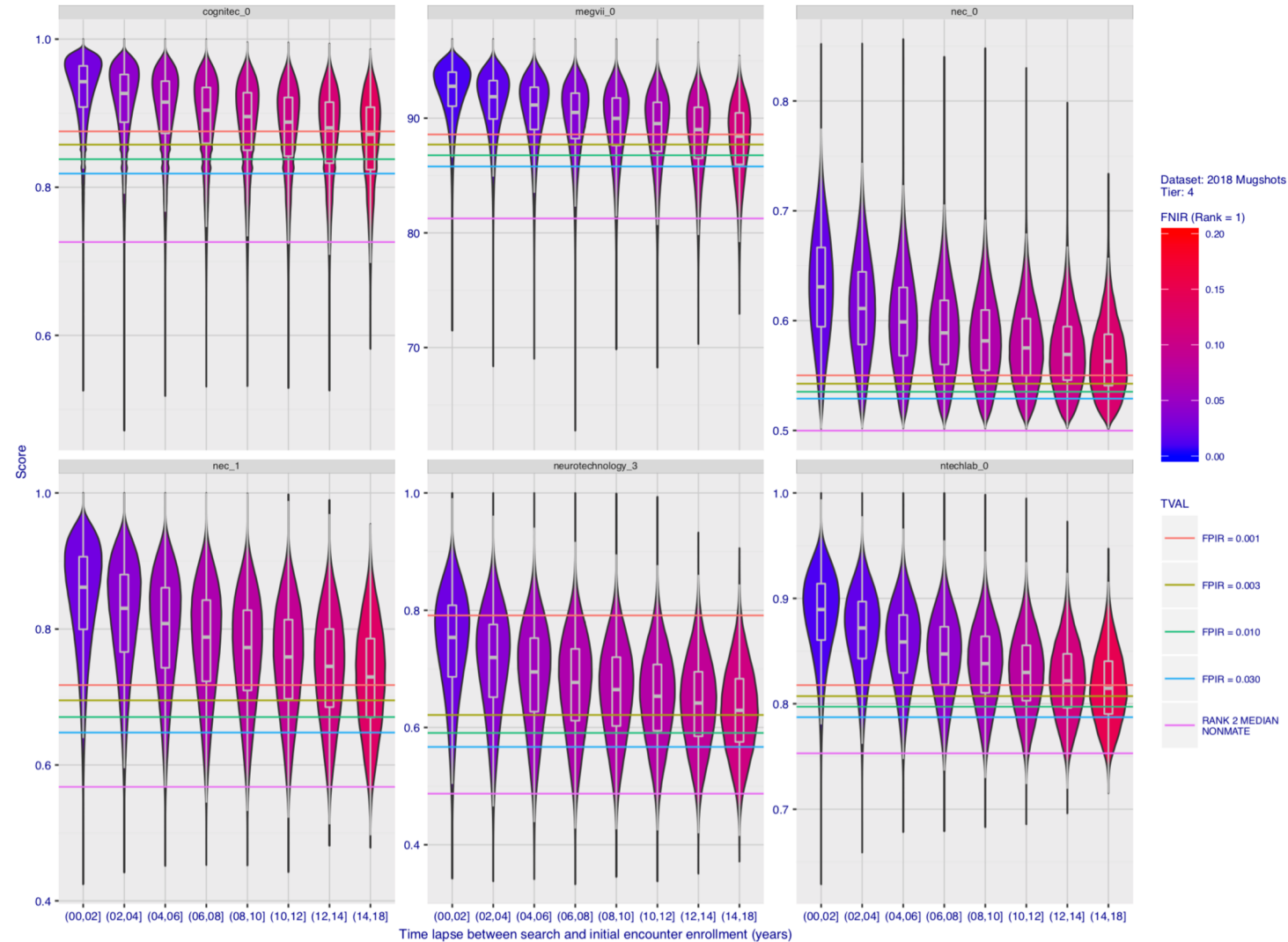


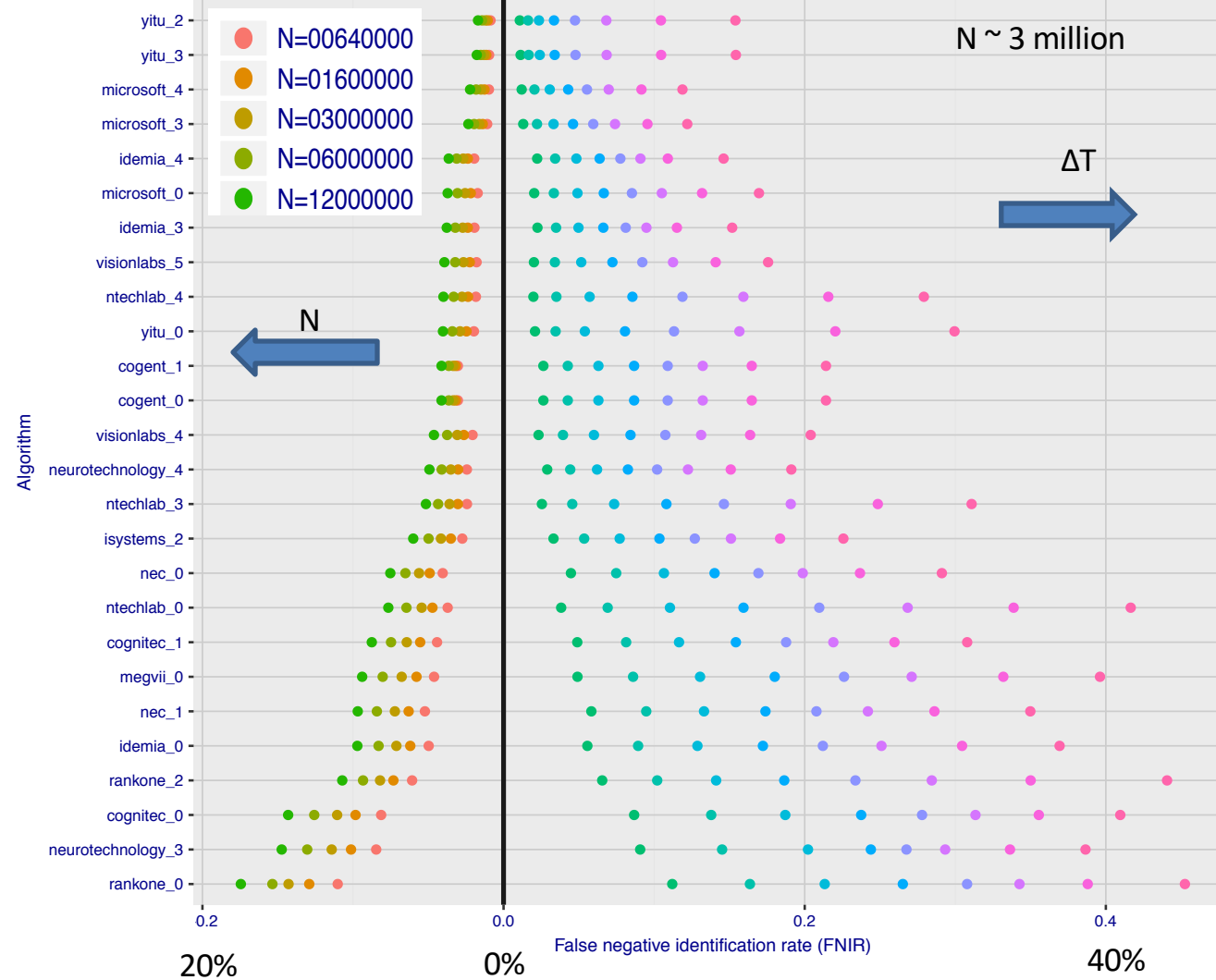
<https://www.bellingcat.com/news/uk-and-europe/2018/09/26/skripal-suspect-boshirov-identified-gru-colonel-anatoliy-chepiga/>

# Mate score distributions under ageing



## Ageing: Further Algorithms





Performance in perspective: What matters more?

1. Algorithm
2. Population size
3. Ageing

- Years Lapsed (00,02]
- Years Lapsed (02,04]
- Years Lapsed (04,06]
- Years Lapsed (06,08]
- Years Lapsed (08,10]
- Years Lapsed (10,12]
- Years Lapsed (12,14]
- Years Lapsed (14,18]

# Children: Age and Ageing

FNMR

Age Variation (Years)

TIME-LAPSE

AGE

Youngest Age of Child In Image Pair (Years)

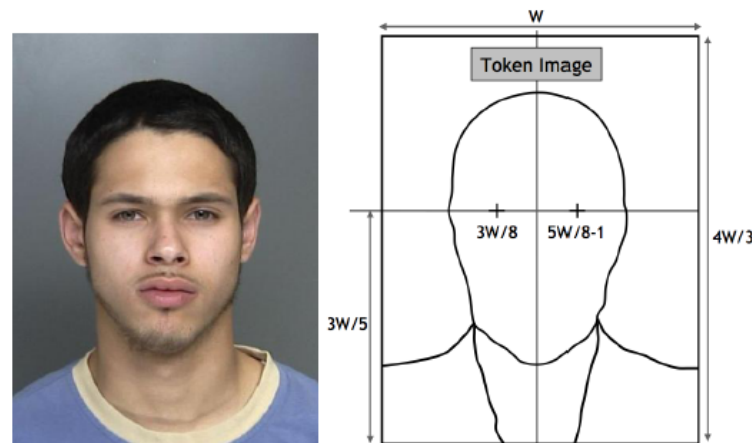
|    | 0                 | 1     | 2     | 3        | 4     | 5     | 6     | 7                | 8     | 9     | 10    |
|----|-------------------|-------|-------|----------|-------|-------|-------|------------------|-------|-------|-------|
| 0  | 0.344             | 0.477 | 0.568 | 0.652    | 0.704 | 0.731 | 0.783 | 0.837            | 0.897 | 0.933 | 0.951 |
| 1  | 0.052             | 0.119 | 0.166 | 0.248    | 0.287 | 0.335 | 0.418 | 0.497            | 0.590 | 0.698 | 0.768 |
| 2  | 0.034             | 0.041 | 0.100 | 0.134    | 0.183 | 0.205 | 0.266 | 0.324            | 0.417 | 0.553 | 0.662 |
| 3  | 0.050             | 0.053 | 0.073 | 0.106    | 0.124 | 0.155 | 0.200 | 0.266            | 0.361 | 0.505 | 0.615 |
| 4  | 0.028             | 0.051 | 0.065 | 0.082    | 0.096 | 0.118 | 0.168 | 0.237            | 0.360 | 0.505 | 0.599 |
| 5  | 0.033             | 0.048 | 0.049 | 0.069    | 0.076 | 0.101 | 0.149 | 0.224            | 0.361 | 0.476 | 0.561 |
| 6  | 0.029             | 0.031 | 0.033 | 0.048    | 0.069 | 0.092 | 0.151 | 0.232            | 0.360 | 0.453 | 0.525 |
| 7  | 0.032             | 0.023 | 0.020 | 0.046    | 0.065 | 0.093 | 0.160 | 0.249            | 0.337 | 0.412 | 0.456 |
| 8  | 0.024             | 0.013 | 0.033 | 0.046    | 0.070 | 0.105 | 0.174 | 0.242            | 0.312 | 0.369 | 0.422 |
| 9  | 0.008             | 0.011 | 0.038 | 0.054    | 0.084 | 0.118 | 0.172 | 0.227            | 0.273 | 0.328 | 0.370 |
| 10 | 0.015             | 0.012 | 0.028 | 0.052    | 0.089 | 0.119 | 0.166 | 0.199            | 0.240 | 0.284 | 0.325 |
| 11 | 0.005             | 0.014 | 0.024 | 0.076    | 0.091 | 0.116 | 0.143 | 0.187            | 0.219 | 0.260 | 0.286 |
| 12 | 0.025             | 0.020 | 0.037 | 0.056    | 0.076 | 0.093 | 0.121 | 0.151            | 0.187 | 0.217 | 0.254 |
| 13 | 0.008             | 0.021 | 0.038 | 0.051    | 0.061 | 0.070 | 0.098 | 0.116            | 0.141 | 0.167 | 0.202 |
| 14 | 0.011             | 0.012 | 0.020 | 0.036    | 0.043 | 0.055 | 0.070 | 0.085            | 0.106 | 0.126 | 0.152 |
| 15 | 0.005             | 0.011 | 0.013 | 0.026    | 0.034 | 0.043 | 0.056 | 0.069            | 0.083 | 0.101 | 0.129 |
| 16 | 0.008             | 0.010 | 0.018 | 0.024    | 0.027 | 0.034 | 0.043 | 0.053            | 0.068 | 0.089 | 0.095 |
| 17 | 0.009             | 0.006 | 0.011 | 0.018    | 0.023 | 0.028 | 0.037 | 0.043            | 0.057 | 0.069 | 0.088 |
|    | Worst Performance |       |       | Midpoint |       |       |       | Best Performance |       |       |       |

D. Michalski, S.Y. Yiu, C. Malec, *The Impact of Age and Threshold Variation on Facial Recognition Algorithm Performance using Images of Children*, ICB 2018, Surfers Paradise.

# Face Image Quality

# Operational backdrop

- Operators seek to collect face reference photos that will support high accuracy face recognition.  
Stored
  - in databases
  - on ID credentials
- Operators often require the reference image be a frontal portrait, conforming to requirements of an ISO standard, ISO/IEC 19794-5.
  - US and UK passports
  - DC driving licenses.
- Quality assessment is often manual (photographer, consular officer), more rarely automatic (with commercial software)



ISO/IEC 19794-5 Token Face Geometry, photometry, behavior are all regulated

Image dimensions, eye and head position are all parametric on  $W$

Alternative standard views possible, in principle, but that ship sailed c. 2004.

# Standards – And deviations from...



ISO Standard



Expression

Gaze

Too close

Pose Angle

## NON-CONFORMANT EXAMPLES

- ISO's idea of "poor" images is better than any image contemplated in Janus.
- ISO aspires to collect reference samples that are pristine, for storage in authoritative databases.



# Janus: Good, bad, wild, ugly, and lots beyond

Declining Quality → Declining Accuracy



\* <http://webstore.ansi.org>

+ <http://www.chicagonow.com/cta-tattler/2013/07/chicago-cops-use-face-recognition-software-to-nab-cta-mugger>

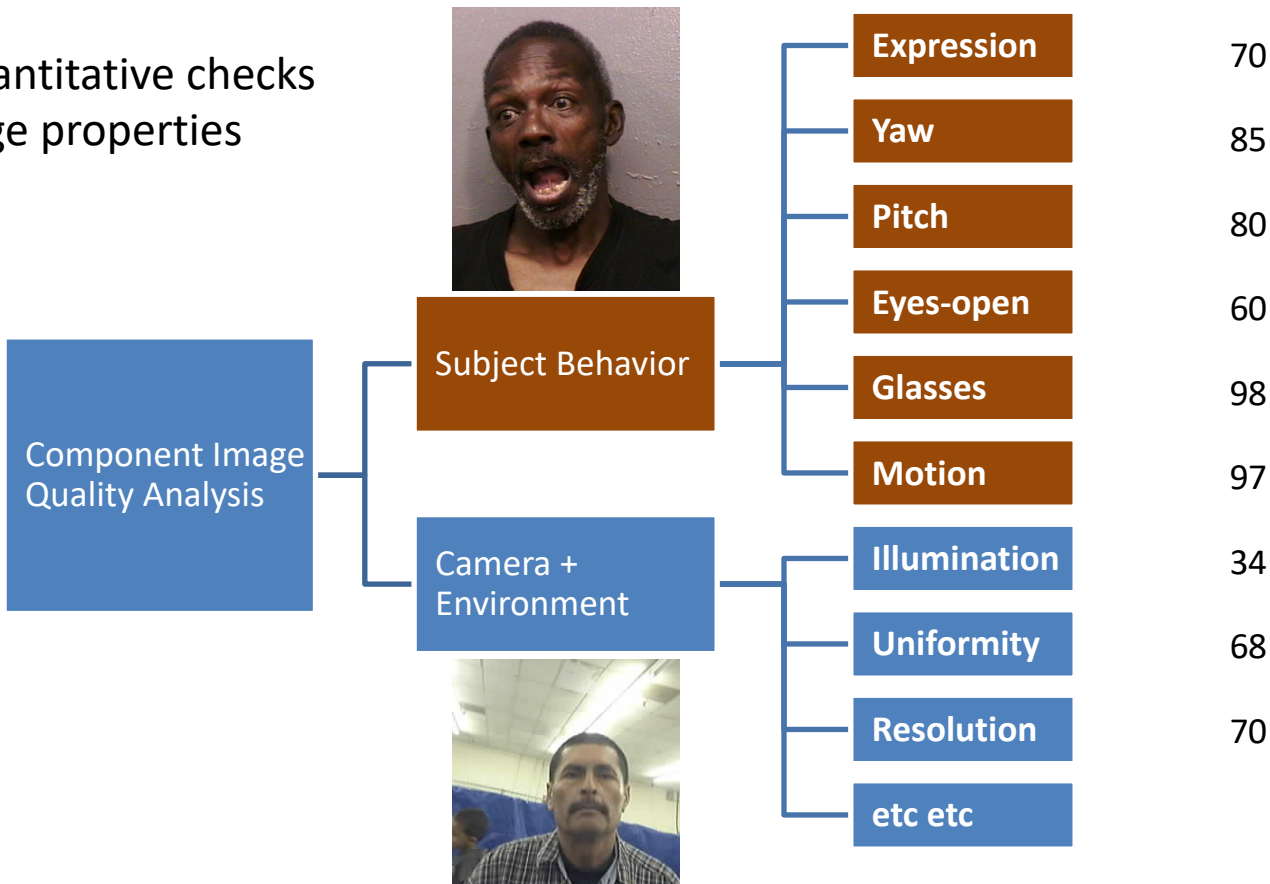
<sup>u</sup> <http://vis-www.cs.umass.edu/lfw/>

<sup>x</sup> <http://io9.com/hidden-faces-can-be-found-by-zooming-into-hi-res-photos-1491607189>

## Part 2: Face Image Quality Vectors

## Face Image Quality Assessment: Standard #2

**Vector Quality:** Quantitative checks of subject and image properties



## Next steps

### » Revise ISO/IEC 29794-5

- Last update was 2010
- Convert from technical report to standard
- Add content
- Align with new criteria in imminent ICAO Portrait Quality standard

### » Timeline:

- Initiate revision 2019-01
- Push content: 2019-06
- Substantially complete: 2020 late
- Publication: 2021

## Part 2: Face Image Quality Vectors

## Operational need:

- Populate authoritative face repositories with photographs that will support high accuracy face recognition.
- The reference photo is widely specified as a frontal portrait, conforming to requirements of an ISO standard, ISO/IEC 19794-5.

**Scalar Quality:** Single value  
Represents utility of image  
to a recognition engine



Q = 95

Q = 85

Q = 62

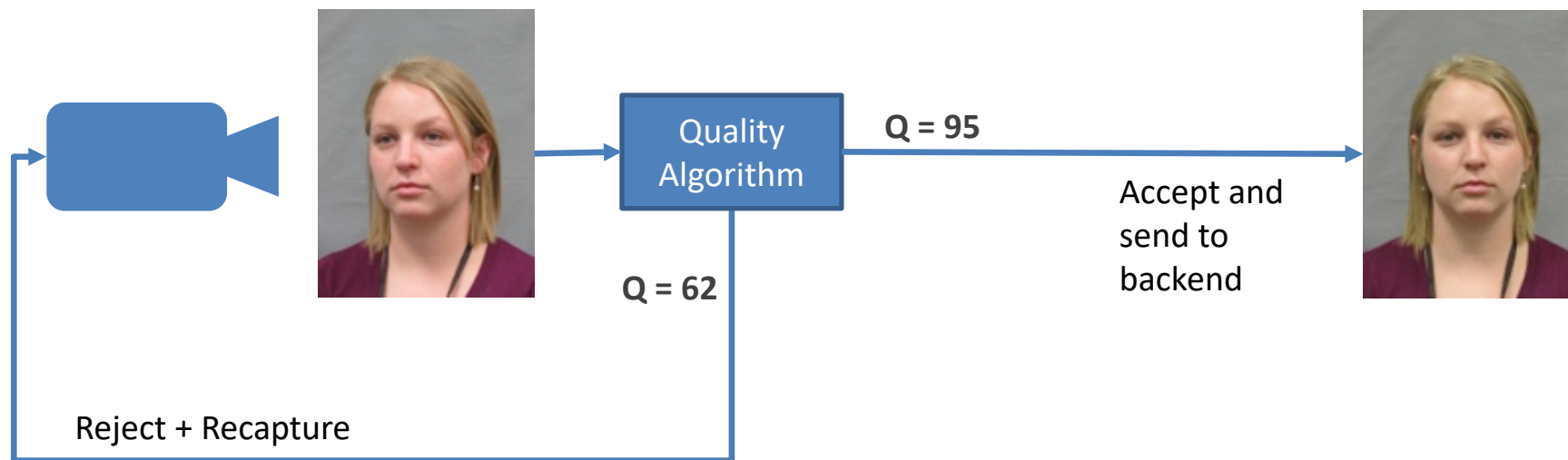
Q = 42

Good

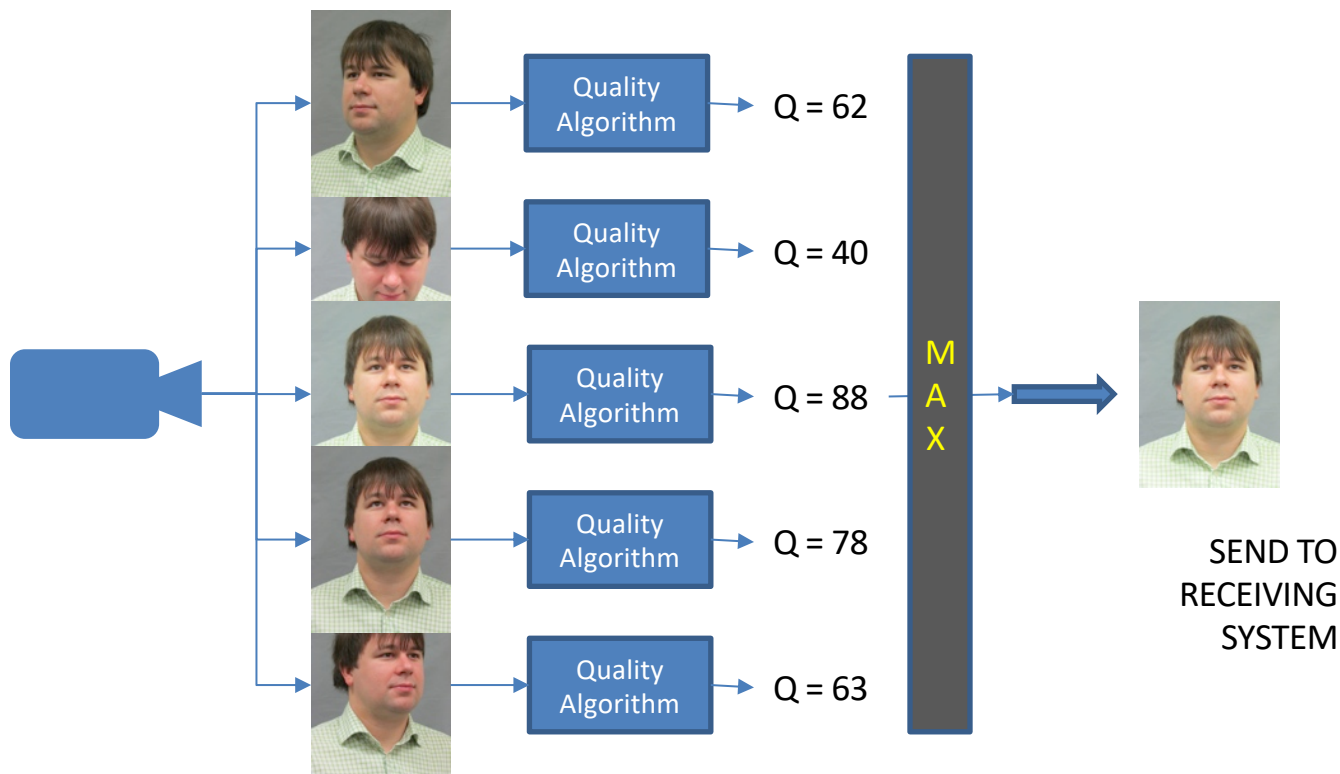
Bad

In fingerprint operations, quality values are used extensively. Sometimes attending operators are paid by based on quality statistics.

# Image quality values use-case 1 of 3: Capture Review



## Image quality values use-case 2 of 3: Best sample selection





## Image quality values use-case 3 of 3: Survey

Identify  
Variation  
Across:

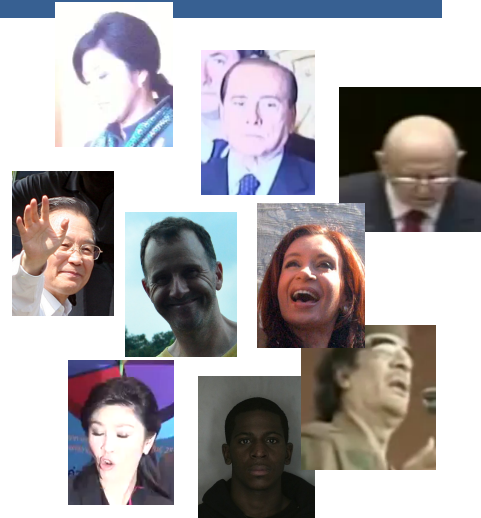
- Locations
- Populations
- Sites
- Camera types



Collection at Airport A  
or  
During Time Period A

**Aggregate Q = 84**

>



Collection at Airport B  
or  
During Time Period B

**Aggregate Q = 53**

And with time

- Trends
- Seasonal
- Diurnal
- ...

## Image Quality Vectors: Use case 2 of 2: Fault Detection

Identify prevalence of image problems across:

- Locations
- Populations
- Sites
- Camera types

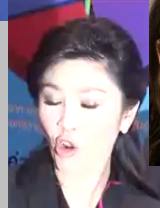
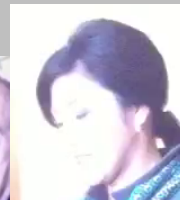
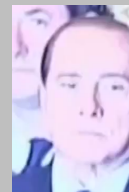
And with time

- Trends
- Seasonal
- Diurnal
- ...



Example 1:  
Specific feedback  
to site

- Glasses



Example 2: Specific  
feedback to site

- Overexposure

## How can quality predict recognition success?

- » A quality algorithm  $F$  operating on an image  $X_1$  produces value
  - $Q = F(X_1)$  [1]
- » Face recognition algorithms compare samples to yield (genuine) scores
  - $S = V(X_1, X_2)$  [2]
- » Quality algorithms **shall** predict  $S$  from  $X_1$  alone.
- » Operating under the assumption that  $X_2$  would be a canonical portrait image i.e. a pristine image of the same subject
  - $Q \sim V(X_1, X_{\text{PORTRAIT}})$  [3]
  - Respects the ISO/ICAO specification as the gold standard for AFR.
  - The light grey text indicates that quality assessment must be done “blind”, targeting a hidden or virtual portrait image
    - cf. blind PSNR in image or video fidelity

## Problem? Scores depend on *two* images: Individual / joint influence of degrading factors

### Covariates where difference matters

$$\text{FRR} \sim F( Q(X) - Q(Y) )$$

- » Facial expression
- » Non-frontal pose (sometimes)



- » Beards on/off; Cosmetics on/off
- » Eye-glasses (rims)

Broadly: Subject behaviors  
influential on facial properties

### Covariates where the worse of two values matters

$$\text{FRR} \sim F( \min(Q(X), Q(Y)) )$$

- » Compression
- » Blur
- » Saturation
- » Contrast, number of grey levels, entropy
- » Occlusion (e.g. sunglasses)

Broadly: Image properties,  
photometric properties

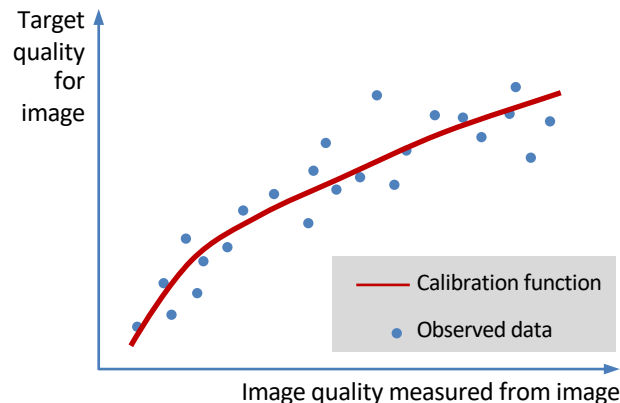
# Performance of an image quality algorithm

## » What: NIST planning an open competition

- Expose poor algorithms i.e. those that produce random numbers
- Find best algorithms i.e. predictors of recognition accuracy
- Calibrate algorithms
  - Make Q scores meaningfully interpretable.
  - Support threshold decisions

## » How:

- Run quality algorithms on LARGE sets of USG data
- Run recognition algorithms too
- Require quality algorithms to target recognition outcomes i.e. prediction



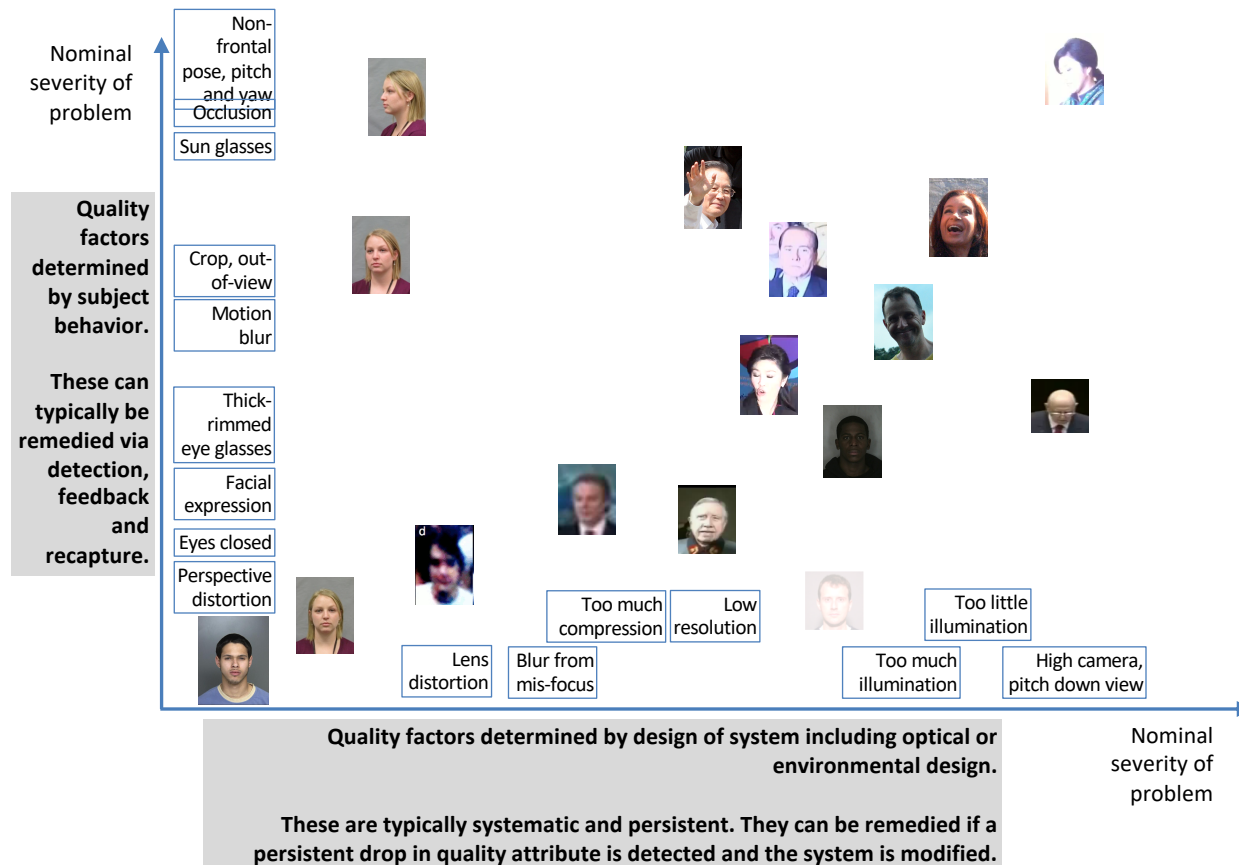
## » When:

- Summer 2018

## » Pre-requisites

- Review and consensus of quality value standard
- Representative large image datasets delivered to NIST

# Subject- vs. Imaging-specific problems



## Part 3: Next Generation Capture Device Standard

# Next generation capture drivers + capabilities

## Background

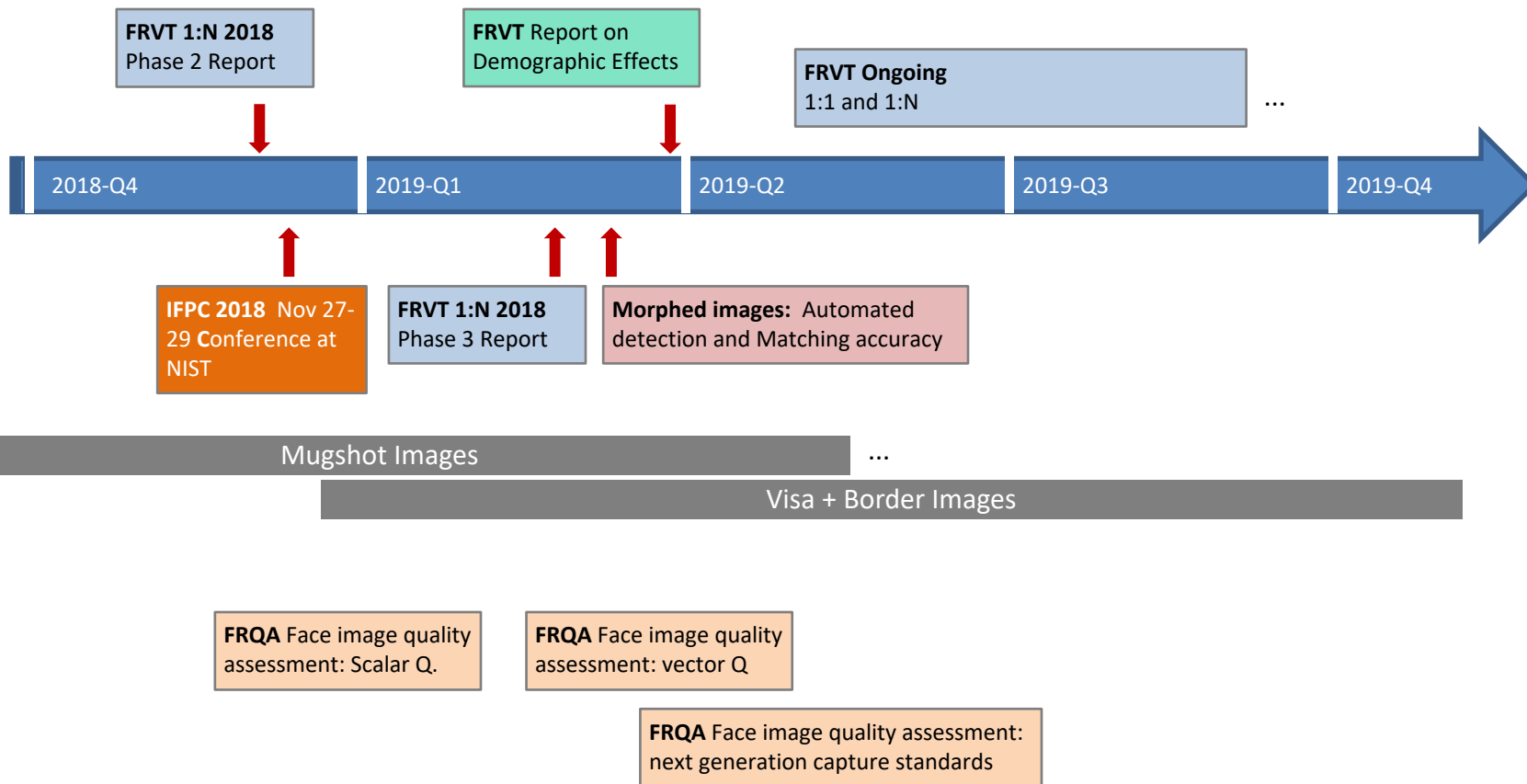
- » Increased reliance on face recognition
- » Increased use globally
- » Unlike fingerprint, iris, most face cameras are “dumb”, unaware of the face itself
- » Many photos deviate from ISO/ICAO
  - Subject appearance
  - Poor imaging
- » Better recognition algorithms
  - But fail with pose, resolution, demographics
- » Human “forensic” adjudication errors
- » New opportunities for image manipulation

## Capabilities

- » Build auto-capture loop into camera
  - Face detector
  - Pose estimator
  - Correct exposure
  - Frontal views
- » Collect high resolution for
  - Forensics adjudication
  - Morph Attack Detection
  - Presentation Attack Detection
- » Collect non-frontal in some applications
- » Prepare lower resolution for auto FR
  - 640 x 480 remains gold standard
- » 3D, for accuracy, attack detection
- » New compression
- » Digital signatures to protect integrity



# Face Recognition Activities at NIST



Thanks

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IARPA / NIST  
Face Recognition Prize Challenge



Face In Video Evaluation (FIVE)

